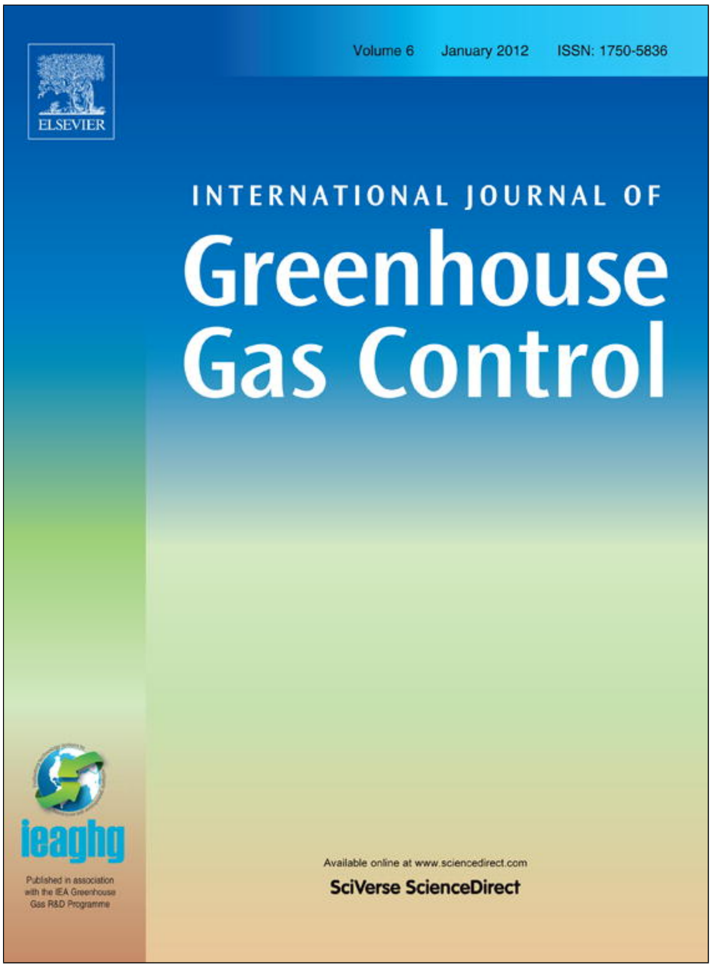
Volume 6 January 2012 ISSN: 1750-5836
ELSEVIER
INTERNATIONAL JOURNAL OF
Greenhouse
Gas Control
ieaghg
Published in association with the IEA Greenhouse Gas R&D Programme
Available online at www.sciencedirect.com
SciVerse ScienceDirect

International Journal of Greenhouse Gas Control 8 (2012) 132–142

Contents lists available at SciVerse ScienceDirect

International Journal of Greenhouse Gas Control

journal homepage: www.elsevier.com/locate/ijggc

Effects of geologic reservoir uncertainty on CO_2 transport and storage infrastructure

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ARTICLE INFO

Article history:
Received 28 July 2011
Received in revised form 9 February 2012
Accepted 10 February 2012

Keywords:
CO_2 storage
Infrastructure
System modelling
Optimization
Uncertainty
Saline aquifers

ABSTRACT

CO_2 capture and storage (CCS) is a climate-change mitigation technology that can significantly reduce greenhouse gas emissions in the near future. To have a meaningful impact, CCS infrastructure will have to be deployed on a massive scale; in the U.S. this will require capturing CO_2 from hundreds of fossil fuel power plants and building a dedicated pipeline network to transport a volume of CO_2 greater than domestic oil consumption. In this paper, we analyze the effect of geologic reservoir uncertainty on constructing CCS infrastructure—geologic uncertainty can impact reservoir cost and capacity estimates by as much as an order of magnitude. This uncertainty propagates through the capture–transport–storage system, influencing decisions including where and how much CO_2 should be captured. We demonstrate the effect of geologic uncertainty using a proposed oil shale industry that could generate tens of millions of tonnes of CO_2 each year. We show that uncertainty can make transport and storage costs deviate by over 100% and that CCS infrastructure, particularly the optimal pipeline network, can considerably diverge spatially. Finally, we draw conclusions on how geologic uncertainty may end up being a driving factor on how major industries decide to manage produced CO_2.

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1. Introduction

CO_2 capture and storage (CCS) is a climate-change mitigation strategy that allows major industry to reduce CO_2 emissions in the near future, while society effectively transitions to a low carbon economy in the longer term (Stauffer et al., 2011a). It also allows nations to continue to utilize existing infrastructure and resources, such as the transmission grid and coal reserves, thus significantly reducing CO_2 emissions without precipitously restructuring the industrial economy. This is especially important due to the large active fleets of coal-burning power plants in major energy producing countries like the U.S. and China. Specifically, CCS technology involves capturing and pressurizing CO_2 at large industrial sources (e.g., fossil fuel power plants, oil refineries, and cement works), transporting the CO_2 in pipelines, and injecting and storing the CO_2 in geologic reservoirs (e.g., depleted oil/gas reservoirs and deep saline formations). Once stored, the CO_2 remains trapped in the subsurface, keeping CO_2 away from the atmosphere for hundreds or thousands of years. CCS applies not only to retrofit at existing industrial CO_2 sources (e.g., IEAGHG, 2011) but also apply to managing CO_2 streams from facilities that use emerging technologies (NETL, 2010a).

For CCS to have a meaningful impact, the U.S. will have to capture, transport, and store billions of tonnes of CO_2 ($GtCO_2$) in the coming decades. This will require massive investment in infrastructure, capturing CO_2 from hundreds of power plants and other industries, and simultaneously matching these CO_2 sources with suitable long-term geologic reservoirs. For the U.S. alone, this investment would annually cost billions of dollars.

Injecting and storing CO_2 currently accounts for a small proportion, perhaps 10–20%, of total CCS costs. But as capture costs come down, storage and transport costs will become increasingly important (Stauffer et al., 2011a). Estimating the CO_2 capacity and injection costs of geologic reservoirs is a challenging and complex problem. Uncertainty in these calculations means that cost and capacity estimations can vary by as much as an order of magnitude (Keating et al., 2011a). Capture and transport technologies, though together much more costly than storage, are much more predictable, especially in terms of estimating CO_2 volumes. The uncertainty in CO_2 storage, though, may propagate throughout a CCS system and end up driving how CCS infrastructure is deployed. For example, a large utility making decisions about how much CO_2 to capture from a selection of power plants might preferentially choose a smaller and more costly storage reservoir with low uncertainty rather than a larger, cheaper alternative that exposes them to the risk of not being able to store all the CO_2 they

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1750-5836/$ – see front matter. Published by Elsevier Ltd.
doi:10.1016/j.ijggc.2012.02.005

produce. Consequently, the success of CCS may ultimately depend on how industry decides to manage the financial and practical risks of storing massive amounts of CO_2 in the subsurface (Esposito et al., 2011).

The effects of uncertainty in geologic properties and processes associated with CO_2 injection and storage have been recognized in terms of site screening (Bachu, 2003), storage capacity (IEAGHG, 2009), brine displacement and management (Buscheck et al., 2011; Surdam et al., 2009; Yamamoto et al., 2009), and the effects of fluid pressures on the regional hydrologic system (Birkholzer and Zhou, 2009). In contrast to petroleum reservoirs, geologic formations investigated for use in CO_2 sequestration may have a higher degree of uncertainty, since the same level of financial incentive for site characterization does not exist. However, the degree of uncertainty in sequestration site characterization can be reduced by gleaning data from oil and gas studies in the region (Venteris and Carter, 2009). The effects of reservoir uncertainty on CCS costs has been investigated by McCoy and Rubin (2009), whose study of several injection case studies concluded that uncertainty in reservoir geology and petrophysical properties controlled overall levelized cost for storage.

In this paper, we demonstrate the effect of reservoir uncertainty on deploying CCS infrastructure. We use the example of a potential oil shale industry in Colorado that could generate 70 $MtCO_2$/yr while producing roughly 1.2 million barrels of oil a day (Mbbl/d) (Keating et al., 2011a). The regulations controlling the development of this unconventional fossil fuel industry are likely to require that the carbon intensity of the resulting transportation fuel is comparable to that of traditional petroleum products (e.g., CRS, 2007); this limitation will require management of CO_2 emissions associated with the generation of gigawatts of electrical power necessary for the leading oil shale processing methods. This study expands upon initial investigations of the effects of reservoir uncertainty on CCS infrastructure previously introduced in Keating et al. (2011b). We use a dynamic CO_2 sequestration system model, *CO_2-PENS* (Stauffer et al., 2009; Viswanathan et al., 2008), to estimate the sensitivity of reservoir cost and capacity calculations to a range of geologic parameters (e.g., porosity, permeability, depth). Using a state-of-the-art CCS infrastructure model, *SimCCS* (Middleton and Bielicki, 2009) we illustrate how uncertainty in storage costs and capacities can drive how CO_2 is transported (pipeline routes and diameters), where CO_2 is stored, and how CCS costs are impacted. Finally, we draw general conclusions on the importance of reservoir uncertainty on CCS activity—and therefore its contribution as a climate mitigation strategy—on a national scale.

2. Background

2.1. CCS on a meaningful scale

CCS will have to be widely deployed on a massive scale to have a meaningful impact on climate change. This will require extensive CCS infrastructure including efficient capture technology, the transportation of large amounts of CO_2 through dedicated pipelines, and extensive low-risk geologic reservoirs. For example, the U.S. share of a CCS climate stabilization wedge (Pacala and Socolow, 2004) requires CO_2 abatement of up to 920 $MtCO_2$/yr,[1] representing 17% of 2009 U.S. total CO_2 emissions (EIA, 2010b). This is equivalent to the CO_2 produced by 245 typical coal power plants—in 2005, the average U.S. coal plant generated 402 megawatts of electricity (MWe) and produced 3.76 $MtCO_2$ (USEPA, 2010). Due to the additional energy required to capture CO_2, abating 920 $MtCO_2$/yr requires managing a larger quantity of CO_2. For instance, a pulverized coal (PC) power plant representative of the average U.S. coal plant (Simbeck and McDonald, 2001) generates 400 MWe without capture technology, producing and emitting 3.16 $MtCO_2$/yr. However, the same PC plant with capture technology installed, and still generating a net 400 MWe, would produce 3.95 $MtCO_2$/yr. Of this, 0.40 $MtCO_2$/yr is emitted to the atmosphere and 3.55 $MtCO_2$/yr is captured (assuming 90% capture efficiency). Therefore, a 920 $MtCO_2$/yr abatement that does not impact net electricity production would actually require CCS infrastructure for 328 power plants and active management of 1164 $MtCO_2$/yr. This amount of CO_2 has a pipeline-ready volume of 1.35 km^3/yr (25 °C and 14 MPa), equivalent to 23.3 Mbbl/d or 24% greater than the U.S. petroleum consumption in 2009 (EIA, 2010a).

2.2. Integrated carbon management

The challenge of capturing, transporting, and storing vast amounts of CO_2 can be met with comprehensive infrastructure models that realistically integrate key decisions on CO_2 capture (where, how much, which technology), transport (routes, pipelines capacities), and storage (which reservoirs, how much CO_2). Such models must incorporate the tradeoffs between scientific, industrial, and policy decisions. The use of carbon-based fossil fuels has been developed and refined over a century, guided by product development and consumer demand; an abrupt change to non-carbon (or reduced-carbon) energy sources over a few decades will require integrated planning and development informed by sophisticated analysis tools. Here, we couple an infrastructure optimization model (*SimCCS*) to a system model for performance and risk assessment of geologic sequestration (*CO_2-PENS*) to investigate the complexities of integrating the capture, transport, and storage system.

SimCCS is a spatial economic-engineering optimization model for planning CCS infrastructure (Middleton and Bielicki, 2009). Results from *SimCCS* can be used by stakeholders, scientists and policy makers to understand how CCS infrastructure could or should be deployed in response to a price on carbon, minimizing infrastructure and management costs, or maximizing captured CO_2. *SimCCS* has been applied to a variety of carbon management scenarios including optimizing CCS infrastructure in California given a range of caps on CO_2 emissions (Middleton and Bielicki, 2009), understanding how oil refinery CO_2 can be used to jumpstart a CCS industry in the U.S. Gulf states (Middleton et al., 2011a), evaluating the cost savings of realistically networked pipelines compared with simple direct source–sink pipelines (Kuby et al., 2011b), optimizing CCS infrastructure in response to a price or tax on CO_2 (Kuby et al., 2011a), and understanding how CCS infrastructure should be dynamically rolled out over time (Middleton et al., 2011b). *SimCCS* has also been adapted to model wind energy infrastructure, simultaneously optimizing wind-generated electricity generation, transmission, and delivery (Phillips and Middleton, 2011).

CO_2-PENS is a hybrid system model for CO_2 sequestration performance and risk assessment (Stauffer et al., 2009; Viswanathan et al., 2008). The model performs probabilistic simulations of CO_2 injection, migration, and leakage in geologic reservoirs and overlying strata. The model samples values for each uncertain parameter from statistical distributions, leading to estimates of global uncertainty that accumulates as the coupled processes interact through time. This study utilizes the feasibility (scoping) mode of *CO_2-PENS*, in which the model provides a built-in, simplified subsurface geometry with constant geologic property values and reduced-form models for CO_2 injection and migration in the reservoir. The injector module calculates injectivity and reservoir capacity to estimate the number of injector wells and associated on-site costs

[1] A global stabilization wedge is equivalent to the abatement of 1000 MtC/yr or 3670 $MtCO_2$/yr, where the U.S. responsibility can be considered proportional to its 25% share of worldwide base load electricity generation.

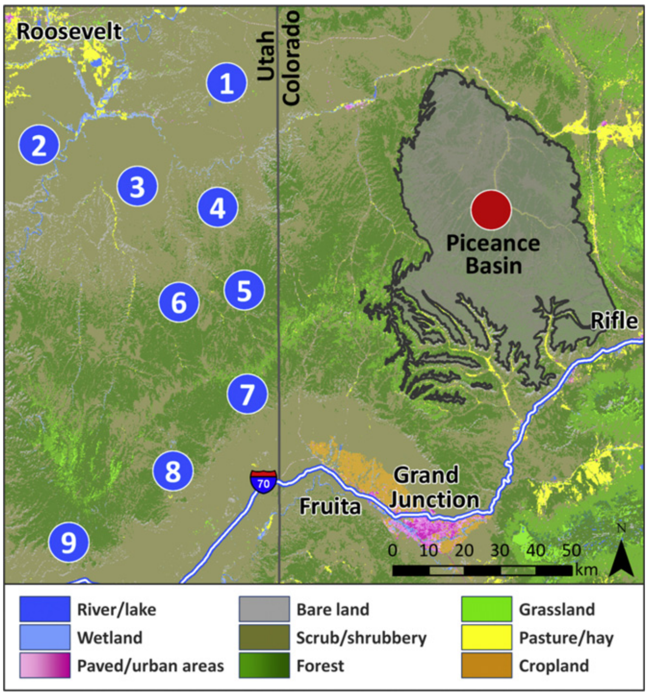

Fig. 1. Overview of the study area. The sink geologic reservoirs are represented by the blue circles. The oil shale industry is represented by a single source (red circle). Landcover (national landcover data) is shown in the background. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

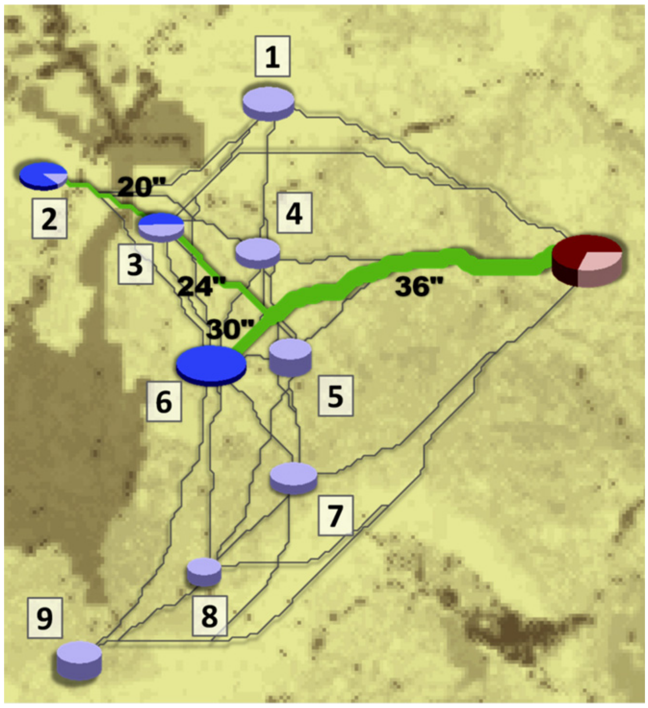

Fig. 2. Spatial deployment of CCS infrastructure for capturing, transporting, and storing 50 $MtCO_2$/yr (Keating et al., 2011a). Each cylinder numbered one through nine corresponds to the geologic sinks in Fig. 1—cylinder area is proportional to sink capacity, height proportional to storage cost, and blue wedges represent the amount of CO_2 stored in each sink for this scenario. For comparison, sink #6 has a capacity of 31 $MtCO_2$/yr and storage cost of \$0.47 tCO_2. The candidate network (grey lines) shows where pipelines can be constructed between the source (red cylinder, maximum production of 70 $MtCO_2$/yr) and sinks. The green lines symbolize the constructed pipeline network; width is proportional to pipeline capacity. The underlying cost surface illustrates pipeline construction and right-of-way costs ranging from low (yellow) to high (brown). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)
Modified from Keating et al. (2011b).

(drilling, distribution piping). The reduced-form injector model utilizes correlations from a full-physics reservoir model to calculate pressure and CO_2 saturation distributions in the reservoir through time (Keating et al., 2011a; Stauffer et al., 2009; Viswanathan et al., 2008).

2.3. CCS and oil shale production

The Piceance Basin in Colorado, USA, contains approximately 1.5 trillion barrels of oil in place in oil shale (Johnson et al., 2009), six times the proven reserves of Saudi Arabia. An oil production rate of 1.5 Mbbl/day over 50 years would require development of only 1–2% of the basin area. Minimizing the carbon footprint—predominantly from electricity production—would require transport and storage of 95–150 $MtCO_2$/yr (Keating et al., 2011a).

A previous study (Keating et al., 2011a) optimized the CCS infrastructure required to manage oil shale CO_2 by coupling two *CO_2-PENS* (geologic reservoir simulation) and *SimCCS* (CCS infrastructure). The study identified nine geologic reservoirs (Fig. 1) capable of storing up to 130 $MtCO_2$/yr; *CO_2-PENS* calculated the capacities and injection/storage costs using its deterministic mode. The CO_2 source term represents aggregate output from power production and gas-stripping for the basin-scale industry (Keating et al., 2011a). The sites vary by area (289–900 km^2), target formation (Castlegate or Entrada Sandstone), depth to the top of the reservoir (average 1500–3500 m), and distance from the oil shale industry in the Piceance Basin. Fig. 2 illustrates a *SimCCS* solution for managing 50 $MtCO_2$/yr from a potential oil-shale industry in the Piceance Basin, Colorado, corresponding to an oil production rate of about 800,000 bbl/day. In this scenario, a 36″ trunk pipeline transports all 50 $MtCO_2$/yr produced westward towards the nine sinks. Shortly before reaching sink #6, the trunk pipeline splits into separate 30″ and 24″ pipelines, delivering 31 $MtCO_2$/yr to sink #6 and 19 $MtCO_2$/yr onwards to sinks #2 and #4. After delivering 7 $MtCO_2$/yr to sink #4, a 20″ pipeline stores the remaining 12 $MtCO_2$/yr in sink #2. Here, the model is trying to utilize the low storage cost of sink #2 (\$0.40/tCO_2—Table 2) while minimizing pipeline costs. Not coincidentally, the 20″ pipeline connecting to sink #2 has a capacity of 12 $MtCO_2$/yr; the *SimCCS* model has minimized costs through economies of scale by maximizing the utility of the pipeline.

2.4. Integrating reservoir uncertainty with carbon management

The previous oil shale study, summarized above and in Fig. 2, was limited to pipeline network designs based on constant values of reservoir capacity and onsite costs for each sequestration site. These constant values were the averages from 100 runs of *CO_2-PENS*. In this paper, we investigate the effects of spatially uncorrelated, variable reservoir capacity and costs among the nine sequestration sites and the resulting effect on source–network–sink design. This uncertainty propagates through the system and impacts how much CO_2 is stored and in which sinks, where and what capacity pipelines are constructed, and the costs of managing the produced CO_2. Because the oil shale industry is represented by a single source producing a known quantity of CO_2, the capture process is not affected by reservoir uncertainty in this study nor does it introduce upstream uncertainties.

3. Reservoir uncertainty

Uncertainty in the performance of geologic sequestration reservoirs results from imperfect understanding of the conditions at various scales, ranging from the shape of individual pores up to the architecture of the reservoir. Variations in reservoir rock composition or texture (e.g., grain size) can produce heterogeneities in pore structure and secondary mineralization, leading to uncertainties in the distribution of permeability and effective porosity. Likewise, geomechanical properties vary according to rock type and secondary mineralization, and heterogeneities and lateral variation may produce uncertainty in the strength and state of stress of the reservoir and caprock, as well as affect the response of the rock to the injection of CO_2 at temperatures and pressures different from those at depth (pre-injection). For example, the injection of cooler CO_2 may produce contraction and fracturing in the reservoir and caprock near the injection well. At the largest scale, the reservoir's ability to retain CO_2 within a structural trap (e.g. dome or anticline) depends on the consistency and continuity of the low-permeability caprock and on the shape and lateral extent of the structure. For instance, the highest elevation of the edge of a structural dome defines the "spill point" where trapped, buoyant CO_2 may laterally exit the reservoir. Lateral changes in lithology and secondary mineralization, as well as the presence of features such as local faults and bedding pinch-outs, can produce reservoir compartmentalization that may result in reduced injection capacity. Lithologic variations in the caprock will control the reactivity of the rock to local CO_2-rich reservoir fluids, potentially either dissolving or dehydrating the seal to produce leakage pathways (Damen et al., 2006). Finally, the variation in fluid chemistry throughout the reservoir system during the injection program may also affect system performance. Many of these physical and geochemical attributes of the reservoir, fluid, and caprock system can be determined adequately during site characterization through drilling, geochemical sampling, borehole logging, and geologic and seismic studies. However, due to the inherent inhomogeneity of natural systems, uncertainty will always remain and will limit our ultimate ability to predict the performance of geologic sequestration reservoirs.

In this study, we focus on the effects of uncertainty in bulk permeability, porosity, and thickness of a reservoir and on the effects of these uncertain parameters on reservoir capacity and injectivity. Geologic formations are heterogeneous in nature, and a property like permeability often varies over several orders of magnitude within the reservoir system (e.g., Bachu and Bennion, 2008). Detailed characterization of these heterogeneities at the scale of interest is not possible in most cases since subsurface studies are by nature data scarce. Sequestration sites are expected to be less well characterized than petroleum reservoirs (since the same level of financial incentive will not exist for CCS); moreover, the benefit of data from existing oil and gas drilling programs to CO_2 sequestration projects has been emphasized (Venteris and Carter, 2009). Petroleum engineering has relied on geostatistical methods to assess the effect of heterogeneity on production calculations. Methods such as kriging and conditional simulations (Viswanathan et al., 2003) are used to generate multiple realizations of synthetic reservoirs to estimate the impact of uncertainty in the system. For CO_2 injection and capacity calculations, the variability in key reservoir parameters can greatly impact the storage metrics of interest, such as amount of CO_2 sequestered (injected and retained) as a function of time.

The geostatistical variability of key parameters can be treated using multiple methods. Rigorous methods incorporate the spatial structure of the reservoir into each synthetic reservoir realization. Conditional simulation techniques can be used to incorporate wellbore data into each realization, and geostatistics are used to populate areas for which no data exist. By including reservoir structure, the method can capture processes such as short-circuiting. An abstraction to this method simply assigns the same permeability to the entire reservoir for each realization but samples the full range of permeability over all geostatistical realizations. The intricacies of processes such as short-circuiting are not captured in detail in this kind of abstraction; however, broad distributions of the key parameters can be defined to capture the overall effect on capacity and injectivity. *CO_2-PENS* incorporates both the rigorous and simplified approaches.

System-level models often neglect the spatial heterogeneity of the reservoir since these models link together numerous spatial and non-spatial processes (e.g. economics, fluid flow, and risk). Systems models require a level of abstraction to make the model both computationally feasible and intuitive. Since numerous parameters are sampled in a system-level model, numerous realizations are required to properly sample the solution space of all the relevant parameters and to calculate the uncertainty in the model outputs. If the system model is too complex and too many parameters are included, the insight that can be gained is greatly reduced, especially for problems that involve sparse data. The system-level model, *CO_2-PENS*, departs from other system models in that it can be run in two distinct modes: a scoping mode for site screening and other data-sparse conditions (Keating et al., 2011a) and a performance-assessment mode for detailed site characterization and coupling to reservoir simulators (Stauffer et al., 2011b, 2009). The performance assessment mode accounts for the spatial heterogeneity of the reservoir, an important consideration once a site has been identified and detailed characterization is required. For this study, detailed data on the spatial structure of the various reservoirs are not available, and we utilize the scoping mode, in which the model provides a simplified subsurface geometry with homogeneous geologic property values for each realization and reduced-form models for CO_2 injection and migration in the reservoir.

We ran two sets of *CO_2-PENS* realizations for each of nine sequestration sites in the Uinta Basin in order to calculate (1) the total capacity ($MtCO_2$) of each site and (2) the number of wells and length of distribution piping required to completely fill[2] the reservoir with CO_2 within 50 years. The sparse data available on reservoir characteristics were used to develop statistical distributions for model inputs (Table 1). Running *CO_2-PENS* in scoping mode, sampled constant values represent homogeneous reservoir parameters for each realization, and Latin Hypercube Sampling and Monte Carlo methodologies ensure that the uncertainty of the combined parameter space is sampled over the course of many model realizations. The uncertain reservoir input parameters in the model are permeability, porosity, and formation thickness (Table 1). Porosity and thickness exert primary control on reservoir capacity, and permeability controls reservoir injectivity (Keating et al., 2011a). Additional uncertainty is specified in economic input parameters, including ranges of unit costs for drilling, distribution piping, and maintenance (Table 1). Uncertainty in the input parameters propagates throughout the model calculations and is reflected in the results (Table 2). For example, uncertainty in reservoir thickness and porosity is reflected in the distribution of reservoir capacity and injection costs over 100 model realizations (Fig. 3).

[2] CO_2 injection is calculated assuming a simple cone-shaped injection plume in an optimized number of injector wells. The reservoir is considered "full" when the plumes from each well intersect. The reservoir capacity calculated in this way is much less (~10%) than the total available pore volume of a rectangular block of the reservoir formation; more sophisticated pressure management scenarios may result in CO_2 filling a greater proportion of the absolute reservoir volume (e.g., Buscheck et al., 2011).

Table 1
Summary of geologic sequestration input parameter values for the CO_2-*PENS* model.

Site[a]	Area (km^2)	Reservoir top depth (m)[b]	Initial pressure (MPa)	Max. pressure[c] (MPa)	Temp.[d] (°C)	Injection rate[e] (Mt/yr)	Permeability (m^2) mean [std dev.]	Porosity mean [std. dev.]	Thickness (m) mean [std. dev.]	Drilling cost ($/km) mean[f]
1	900	2000	20	30	62	17	8e−15 [3e−15]	0.26 [0.05]	50 [10]	939,000
2	486	3500	34	52	101	15	8e−15 [3e−15]	0.26 [0.05]	50 [10]	2,100,000
3	594	2500	25	37	75	13	8e−15 [3e−15]	0.26 [0.05]	50 [10]	1,270,000
4	660	2000	20	30	62	12	8e−15 [3e−15]	0.26 [0.05]	50 [10]	939,000
5	750	1500	15	22	49	11	8e−15 [3e−15]	0.26 [0.05]	50 [10]	726,000
6	812	3000	29	44	88	31	3.6e−13 [5e−14]	0.25 [0.05]	77 [10]	1,670,000
7	504	2000	20	30	62	13.5	3.6e−13 [5e−14]	0.25 [0.05]	77 [10]	939,000
8	289	1800	18	27	57	7	3.6e−13 [5e−14]	0.25 [0.05]	77 [10]	838,000
9	576	1500	15	22	49	12	3.6e−13 [5e−14]	0.2 [0.05]	77 [10]	726,000

[a] Sites 1–5 inject into the Castlegate Sandstone, and sites 6–9 inject into the Entrada Sandstone.
[b] Average reservoir top depth for dipping strata.
[c] Maximum pressure is set at 70% of lithostatic pressure to avoid hydrofracturing the caprock.
[d] Reservoir temperature is calculated from a surface temperature of 10 °C and a geothermal gradient of 26 °C/km (Blackett, 2004; Henrikson and Chapman, 2002).
[e] Injection time is 50 years, followed by 50 years of relaxation.
[f] Drilling costs are calculated according to methods outlined in Keating et al. (2011a) and Stauffer et al. (2009). Standard deviation values for drilling cost, well maintenance cost, and distribution pipe maintenance cost are equal to one-tenth of the mean.

Reservoir capacity and well injectivity are calculated in CO_2-*PENS* using a multivariate response surface (Letellier et al., 2010) based on a library of several thousand runs of a full-physics, multiphase CO_2-brine numerical model, *FEHM* (Zyvoloski, 2007; Zyvoloski et al., 1997). Important reservoir parameters for this response surface include permeability, pressure, thickness, domain radius, and injection rate. Reservoir permeability exerts strong control on the injectivity, number of injector wells, and on-site costs. We specified a log-normal distribution for Castlegate Sandstone permeability in CO_2-*PENS*, and the distribution (as well as distributions of other uncertain parameters) was sampled over the course of 100 realizations using a Monte Carlo approach. In order to investigate the effect of the statistics of the permeability distribution on model results (i.e. costs) we varied the mean and standard deviation (Fig. 4). The base value for the mean is 8×10^{-15} m^2 (8 milliDarcies, mD) with a standard deviation of 3×10^{-15} m^2. As the mean permeability declines below 1×10^{-14} m^2 (10 mD), the injectivity is reduced and onsite costs rise rapidly (Fig. 4a and b). A wide permeability standard deviation (i.e. 1×10^{-14} m^2) produces a wide range in costs—from $0.05 to $6.65 per tCO_2 (Fig. 4c and d). As the standard deviation decreases below 1×10^{-15} m^2, the range of costs tightens to a minimum—$0.40 to $1.18 per tCO_2; this minimum range is related to variation in other model parameters, such as cost of drilling.

The base model values for Castlegate permeability mean and standard deviation are located at the transition where costs begin to rise from their steady minimum values to increase rapidly as permeability and injectivity decline. It is apparent from Fig. 4 that either a low reservoir mean permeability or a wide standard deviation will produce a high uncertainty in on-site costs, spanning an order of magnitude. This cost uncertainty drives uncertainty and variability in the design of CCS infrastructure. The uncertainty in reservoir permeability can be a function of natural variation in the formation (aleatory uncertainty), a lack of data (epistemic uncertainty), or both. The shape of the distribution may depart from a simple normal curve due to fracture or solution pathways that emphasize higher permeability or cementation and diagenesis that decrease permeability. To some extent, the more information available to characterize a potential sequestration site, the lower the epistemic uncertainty, and the better the prediction of storage costs that can be made.

4. Infrastructure variability

The *SimCCS* model is parameterized by data describing the costs and CO_2 capacities to capture, transport, and store CO_2. The model can deploy CCS infrastructure in three ways: in response to a price to emit CO_2, to maximize captured CO_2 within a fixed budget, or to minimize infrastructure costs to capture a set amount of CO_2 (e.g., within a cap- and trade environment). In this study, we use *SimCCS* to capture a predefined amount of CO_2 produced by a potential oil shale industry. Each sink is defined by the cost to inject and store CO_2 over a 50-year project length. The model is also given a potential set of arcs or routes where pipelines could be built (grey lines in Fig. 2); this candidate set of arcs is extracted using the methodology described in previous studies (Middleton and Bielicki, 2009; Middleton et al., 2012). *SimCCS* identifies the optimal set of CCS infrastructure to capture and store the CO_2 produced by the oil shale industry. This involves making decisions regarding (i) which sinks should be used and (ii) how much CO_2 to inject/store; (iii) which potential arcs should pipelines be constructed and (iv) and what diameter; (v) how much CO_2 should be transported through each pipeline; and (vi) how the CO_2 should optimally be allocated between the oil shale industry and the nine sinks. All these decisions are highly interdependent and so they

Table 2
Summary of results of 100 *CO_2-PENS* realizations for each of the nine sinks. Injection-storage costs include (i) distribution pipeline costs as described in Keating et al. (2011a), (ii) well maintenance costs ($15000/well/year), and (iii) pipe failure repair costs (mean is $50000/event, standard deviation is $20000/event).

Sink ID	Injection capacity[a] ($MtCO_2$/yr)				Cost[a,b] ($/t$CO_2$)			
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max
1	16.3	4.8	5.6	28.8	0.69	0.27	0.17	1.80
2	14.4	4.3	4.9	25.5	0.40	0.16	0.11	1.05
3	13.0	4.0	4.4	22.9	0.55	0.22	0.15	1.44
4	12.0	3.6	4.1	22.2	0.70	0.27	0.17	1.81
5	10.9	3.2	3.7	19.3	1.20	0.47	0.28	3.11
6	31.0	7.9	9.2	49.7	0.47	0.18	0.11	1.08
7	13.5	3.5	4.0	21.8	0.71	0.27	0.16	1.59
8	7.1	1.8	2.1	11.5	0.85	0.32	0.20	1.91
9	12.4	3.2	3.7	19.9	1.21	0.46	0.27	2.73
Total	130.6			Avg.	0.70			

[a] Injection capacity and cost values are based on *CO_2-PENS* modeling results reported in Keating et al. (2011a).
[b] On-site costs include costs for drilling new injector wells, refurbishing existing wells for use as injectors, and distribution piping to the wellheads.

have to be considered simultaneously. Typically, *SimCCS* optimizes two additional decisions; whether sources should capture CO_2 and how much. However, these two decisions are predetermined in this present study since a single source represents the oil shale industry in the Piceance basin.

In order to investigate the impact of reservoir uncertainty on CCS infrastructure, we execute the *SimCCS* model 100 separate times for 14 different carbon management scenarios ranging from 5 to 70 $MtCO_2$/yr (80,000 to 1.1 Mbbl/d). Each of these 1400 *SimCCS* runs randomly selects a linked cost and capacity from the 100 *CO_2-PENS* realizations for each of the nine sinks; there is no spatial correlation between the nine reservoirs. Consequently, each carbon management scenario has 100 solutions that can differ in terms of the cost to transport and store CO_2, which sinks and pipelines are constructed, and how the CO_2 flows between the source and sinks.

Straightforwardly, sink costs will directly influence the total carbon management cost—for example, uniformly high sink costs will drive up total CCS costs. Sink capacities also impact costs; the model has to balance the search for lower costs with a need for identifying the desired total CO_2 storage capacity. For instance, a reduction in the capacity of cheaper sinks can have an effect similar to increasing the average storage cost for all nine sinks. Changes in sink capacity also cause the model to look for different pipeline solutions to transport all of the captured CO_2. Consequently, variations in the costs and capacities of the sinks, such as those calculated with *CO_2-PENS*, will potentially change both the costs and spatial deployment of all CCS infrastructure.

4.1. Spatial variability

Every infrastructure solution generated by *SimCCS* in this study is unique. That is, each of the 100 solutions for the 14 management scenarios differ in terms of total cost, amount of CO_2 stored in each sink (if any), pipeline routes and capacities, and/or CO_2 flows between the source and sinks. There is a high level of variety in solutions; for example, the 100 *SimCCS* runs in the 70 $MtCO_2$/yr carbon management scenario produced 35 unique combinations of the nine sinks to meet the 70 $MtCO_2$/yr target. Fig. 4

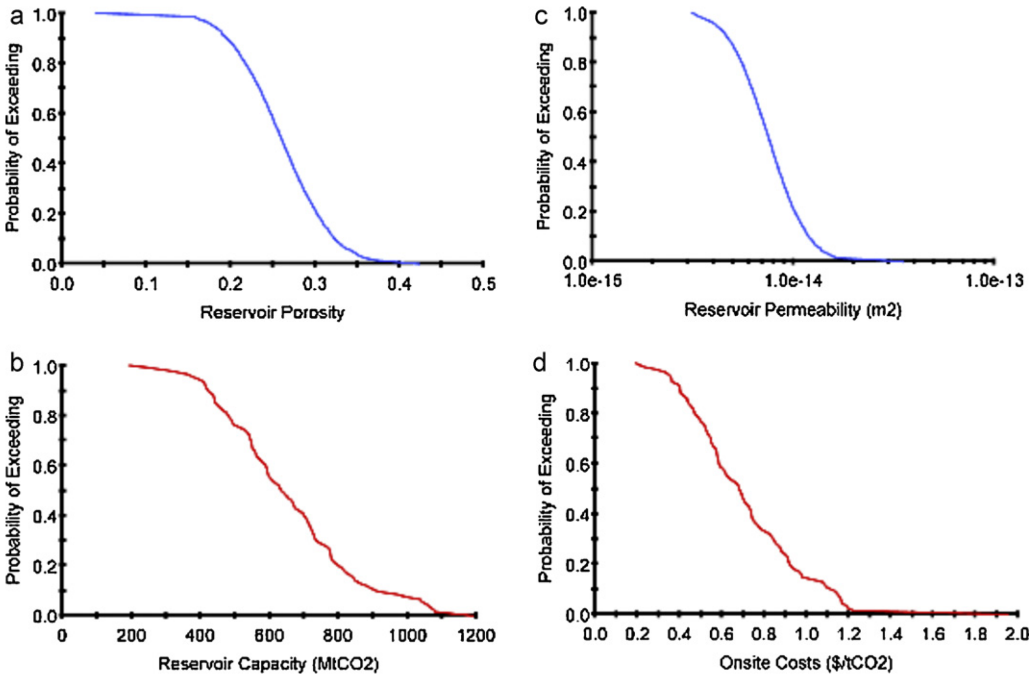

Fig. 3. Complementary cumulative distribution functions (CCDFs) for input (blue) and output (red) parameters reflect 100 *CO_2-PENS* model realizations of sequestration site #1. Reservoir porosity (a) is one parameter that controls calculated reservoir capacity (b), and permeability (c) determines numbers of injector wells and the majority of onsite costs (d). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

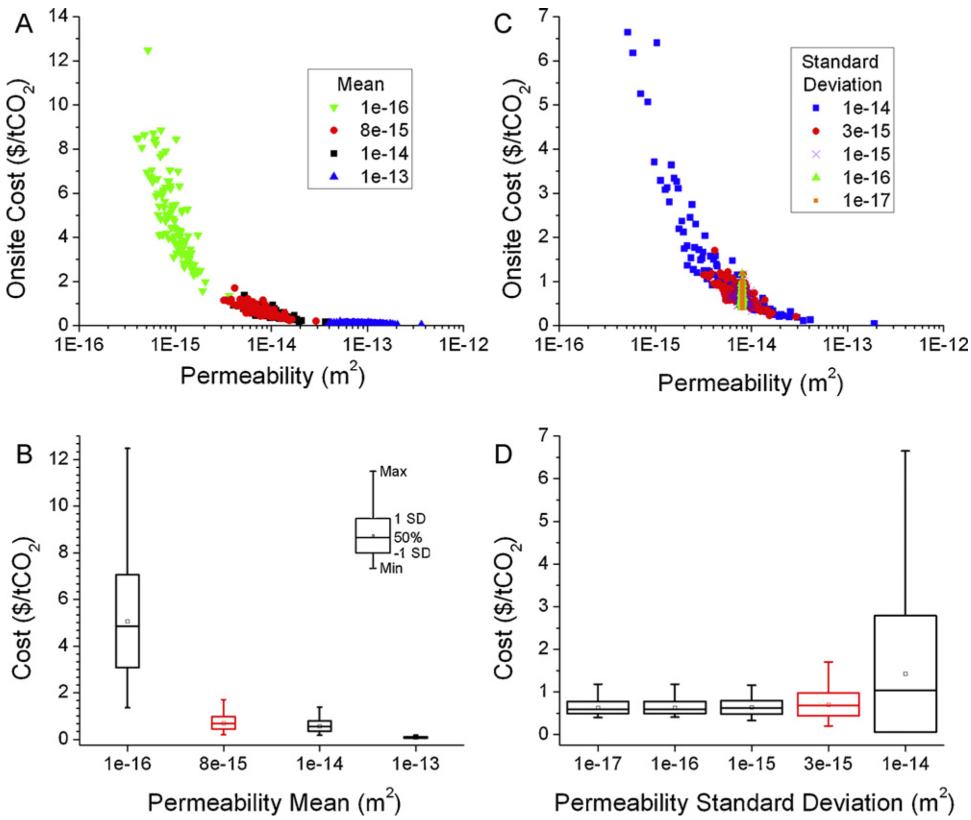

Fig. 4. Variation in on-site cost ($/tCO$_2$) with changes in the permeability distribution (m^2). (A, B) Mean permeability varies over several orders of magnitude, with standard deviation equal to 0.375 times the mean. (C, D) Variation in standard deviation, with mean equal to 8×10^{-15} m^2. Each model run (colors) consists of 100 realizations sampled from the distribution by *CO$_2$-PENS* using a Monte Carlo method. Model base values for Castlegate Sandstone are log-normal with mean 8×10^{-15} m^2 and standard deviation 3×10^{-15} m^2, shown in red symbols. The base model values are located at the transition from flat to rapid increase in costs vs. permeability. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

illustrates representative solutions for the six most common combinations, accounting for over half of the 100 realizations. Fig. 4a, for instance, illustrates a set of four sinks (#2–3–4–6) that appear in 16 *SimCCS* solutions. Even though each of these 16 realizations use the same set of sinks, the amount of CO_2 stored in each sink CO_2 (blue wedges), the pipeline capacities (arc widths), and the pipeline routes vary widely between solutions. The model adapts the pipeline capacities, pipeline routes, and CO_2 flows in order to maximize economies of scale in transportation (i.e., fully utilized pipelines have lower unit costs) and deliver as much CO_2 as possible to the cheapest sinks.

There are also many commonalities that can be identified across the different solutions. For example, the combination of sinks #2–3–6 is present in 72 of the 100 different solutions. This suggests that these three sinks could form a robust core for any infrastructure solution, providing the type of low-risk solution that would satisfy a utility's goal of safely disposing their CO_2 emissions. This three-sink combination occurs so frequently because they simultaneously offer three distinct advantages: they have a large cumulative capacity (~58.4 MtCO$_2$/yr on average), they offer relatively low-cost cost storage (sinks #2 and 6 are the two cheapest sinks), and they are spatially proximal to each other which minimizes pipeline connection lengths. In contrast, the combination of sinks shown in Fig. 5b (sinks #1–2–3–6) is markedly different from the other five frequently selected sink combinations. For example, because sink #1 is utilized but without sink #4 being present, the major trunkline leaving the source trends northwest (as opposed to westward). In these realizations, sink #1 has a cost significantly below its average for the 100 *CO$_2$-PENS* results (see Table 2). Because the results shown in Fig. 5b appear to be an outlier, it is likely that this combination of sinks and pipeline routes/capacities is not a robust solution for capturing and storing CO_2.

Studying the 100 *SimCCS* solutions in aggregate further reveals which sinks and pipelines are likely to provide a robust solution for safely disposing CO_2. For example, sink #6 appears in 98 of 100 *SimCCS* solutions for the 70 MtCO$_2$/yr scenario (Fig. 6). This is not unexpected since sink #6 is, on average, the largest (31 MtCO$_2$/yr) and second cheapest sink ($0.47 tCO$_2$) in the dataset. Subsequently, the *SimCCS* model is always likely to utilize this low-cost abundant-capacity (Fig. 6). Conversely, sink #9 is selected in just one *SimCCS* solution; sink #9 is an expensive sink and, because it is spatially dislocated from cheaper and larger sinks, it requires an extensive set of pipelines to be reached. The number of times pipelines are constructed, and with what capacity, also suggests which pipelines provide a reliable network for managing CO_2. For instance, the large red pipelines in Fig. 6 are likely to form a strong backbone to any pipeline network regardless of sink uncertainty.

4.2. Cost variability

SimCCS deploys infrastructure in a cost-minimization framework in order to satisfy a CO_2 cap or target, stay within a carbon price, or satisfy and economic budget. The spatial infrastructure changes highlighted above are driven by the model striving to minimize costs while remaining within other constraints. Consequently, the CCS infrastructure costs within each carbon management scenario fluctuate with sink uncertainty. Fig. 7 highlights how costs (total, transport, and storage) vary with both increasing CO_2 targets and uncertainty. As the CO_2 target is increased from 5 to 70 MtCO$_2$/yr, total infrastructure costs rise—managing more CO_2

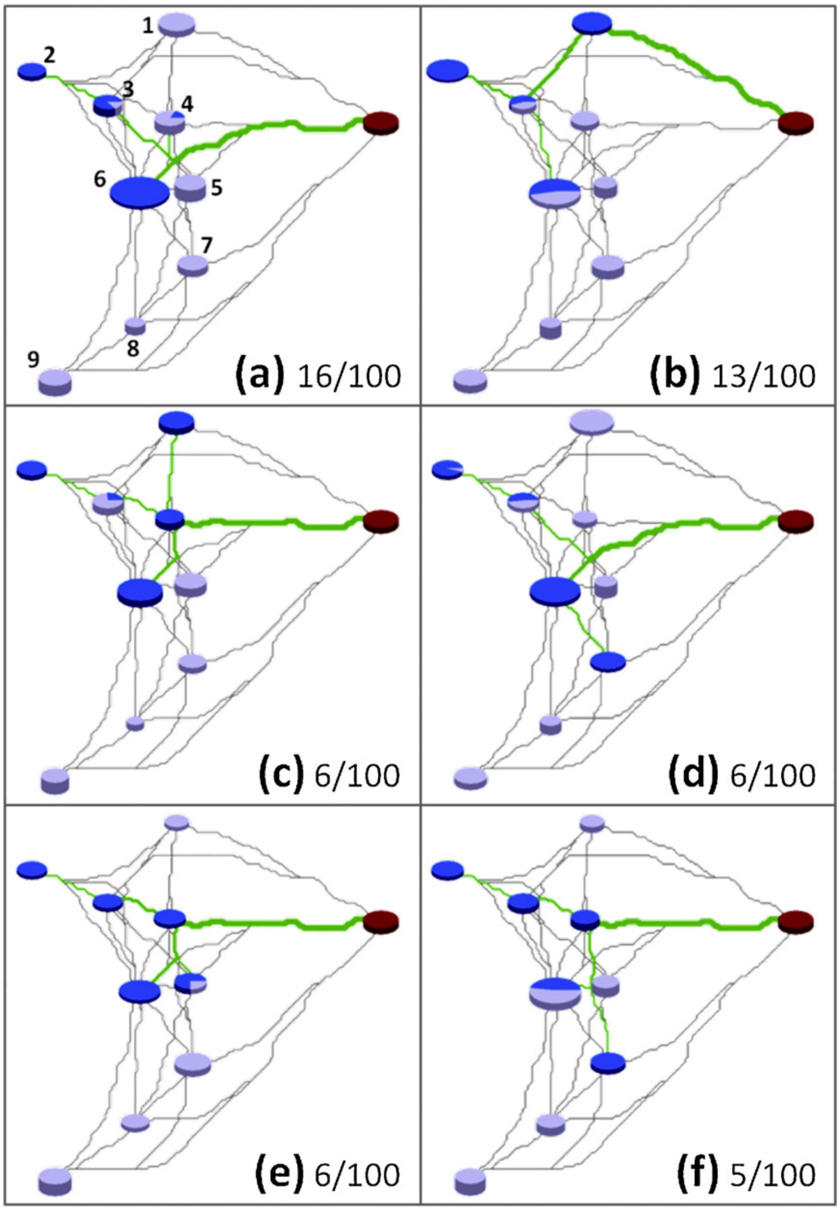

Fig. 5. Six most frequent combination of sinks for the 70 $MtCO_2$/yr scenario, ranging from most (a) to least common (f). Each of the six subfigures displays a representative solution for each unique set of sinks.
Modified from Keating et al. (2011b).

requires more pipelines and more injection wells in more sinks. However, the unit costs have a more complex relationship with CO_2 amounts. In short, as the CO_2 target rises towards 70 $MtCO_2$/yr, the average pipeline costs decrease through economies of scale, and the average storage costs slightly rise as more expensive sinks are utilized. For example, the 100 runs for the 5 $MtCO_2$/yr target typically require a single 16″ pipeline joining the single source to sink #6; this pipeline costs \$6.0 M/yr to construct and operate, equivalent to \$1.2/tCO_2. The 100 model runs for the 30 $MtCO_2$/yr target also often build a 30″ pipeline using the same route at a cost of \$10.9 M/yr, amounting to \$0.36 tCO_2/yr. This reduction in costs (\$1.2/tCO_2 compared with \$0.36/tCO_2) is achieved through economies of scale: ROW costs are almost impervious to pipeline capacity, and fully utilizing a larger pipeline is always cheaper than constructing a smaller pipeline. Beyond 30 $MtCO_2$/yr, pipeline costs flatten out since the vast majority of the pipeline network operates at close to full utilization (see the solid line in Fig. 7c). Generally, average transport costs in this study are lower than for other studies due to the close proximity of the nine sinks and the ready access to federal and other low-cost land with few geographical impedances. For instance, there is an almost entire lack of paved roads and urban areas situated in between the oil shale industry source and the nine sinks, with landcover dominated by scrubland, forestry, and bare rock (Fig. 1).

Uncertainty complicates the relationship between the amount of CO_2 being managed and the infrastructure costs. For example, total costs (Fig. 7) for targets greater than 20 $MtCO_2$/yr have transport and storage costs that vary by more than 100%. For the 55 $MtCO_2$/yr scenario, this translates into a range of \$0.5 to \$1.2/tCO_2. For representative projects with higher transport (e.g., areas with higher populations and less federal land) and storage costs (e.g., sinks with less favorable geology), costs could range between \$5 and \$10/tCO_2 (e.g., Middleton et al., 2012). At these values, sink uncertainty could significantly impact the likelihood

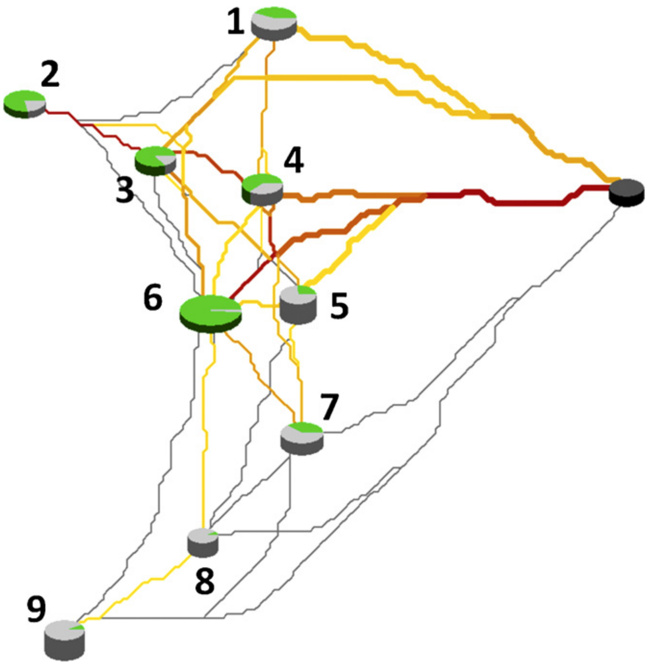

Fig. 6. Aggregate overview of 100 *SimCCS* runs for the 70 $MtCO_2$/yr carbon management scenario. The width and height of each sink–cylinder represents average CO_2 capacity and cost respectively. The green sectors depict the proportion of times, out of 100 runs, that each sink is selected. The arc colors represent the frequency that each arc is selected by *SimCCS*, ranging from yellow (selected just once in 100 runs) through to red (selected 82 times). Arc width is proportional to the average pipeline capacity *when that arc is selected*—the smallest width represents a 12″ pipeline (2.35 $MtCO_2$/yr capacity) and the largest a 42″ pipeline (83.95 $MtCO_2$/yr). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

of how, or even whether, a CCS project is implemented. The *SimCCS* pipeline modeling in this study is exposed only to uncertainty in storage capacity and cost; the pipeline costs vary only in order for the model to take advantage of cheaper sinks. As a result, the range of pipeline costs (Fig. 7c) is limited and the variability in total costs is therefore driven by the storage costs (Fig. 7b). As the carbon management scenarios capture more CO_2, the network length predictably increases. In addition, the variability in network lengths also increases, though without affecting the transport costs beyond 30 $MtCO_2$/yr. The cost impact is minimal because the *SimCCS* model can fully utilize the pipeline network whether it requires longer-but-smaller pipelines or shorter-but-larger pipelines to transport the CO_2 between the source and sinks.

5. Discussion

Geologic uncertainty has a significant impact on the spatial deployment of CCS infrastructure. The variation in CO_2 transport and storage costs alone exposes utilities to risks that they must minimize, risks that could be the make-or-break of CCS on a meaningful scale. Capture technologies dominate CCS in terms of cost, though it is likely that these costs will continually decrease with new technology while transport and storage costs remain steady (Stauffer et al., 2011a). As a result, geologic uncertainty will play an increasing role in CCS development in the next decade or two. There is also much less flexibility for optimizing capture decisions, and therefore reducing costs, within a comprehensive CCS network. Industrial sources are immovable, and therefore costs cannot be reduced through spatial optimization of infrastructure. Further, capture technology decisions (e.g., oxyfuel retrofit versus post-combustion capture) are largely independent of the remainder of the CCS infrastructure network, and therefore it is difficult to uncover cost savings through infrastructure integration. Consequently, system-wide cost savings and risk reduction may be driven in large part by uncertainty in the geologic reservoirs.

Thorough site characterization can serve to minimize epistemic uncertainty and can support more robust predictions of reservoir capacity and injection behavior during the lifetime of the site (NETL, 2010b). The level of investment in site characterization activities may vary from site to site depending on the complexity of the geologic setting, proximity to population centers, or regulatory demands. The operator of a network of CO_2 sources

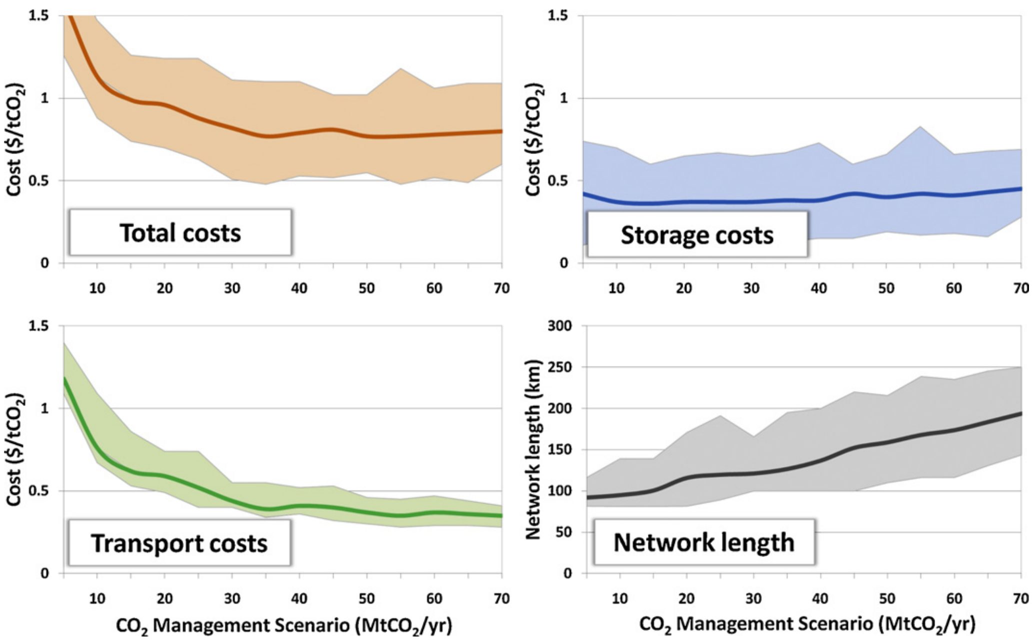

Fig. 7. Cost and network variability for 5–70 $MtCO_2$/yr scenarios. Each solid line indicates the mean solution costs/network length, and the areas represent the range (min/max) values for the 100 *SimCCS* runs.
Modified from Keating et al. (2011b).

and sinks may choose to minimize site characterization costs and assume greater risk of unexpected performance at a particular sink if there is flexibility for reconfiguring the CCS infrastructure (e.g. pipelines). Reduced site characterization costs may result in higher project costs elsewhere, such as enhanced monitoring, verification, and accounting (MVA) to ameliorate uncertainty in leakage risk. A potentially greater impact, however, is the effect of reservoir uncertainty on the overall performance of the CCS system over its operating lifetime.

Geologic uncertainty has an impact beyond straightforward costs. Knowledge about a carbon reservoir will increase as CO_2 is injected and stored over a number of years and changes are measured in storage capacity and injection costs. The evolving estimates of cost and capacity might present significant challenges, as well as opportunities, to the existing infrastructure. For example, estimated reservoir capacities may rise and/or injection costs may fall as more is learned as the project progresses. If the CCS infrastructure network is flexible, such as incorporating excess pipeline capacity, it may be possible to divert more CO_2 to such an underestimated sink. Conversely, negative changes in reservoir performance will detrimentally affect CCS operations. This could be a simple rise in costs resulting from lower-than-expected permeability and the need for additional injection wells. Or, more acutely, reduced reservoir capacity (e.g., due to low porosity) could leave CO_2 stranded at one or more sources, particularly if the pipeline network is close to full utilization. In a carbon-constrained economy, this stranded CO_2 would incur a cost to emit or require purchase of additional CO_2 permits. In the medium to long term, this outcome could be remedied through further infrastructure investment: constructing new pipelines, expanding operations at existing reservoirs, and opening up new sinks. Naturally, the modified CCS infrastructure network (sources, pipelines, sinks) will cost more than originally anticipated and perhaps not perform as effectively.

An understanding of how large-scale CO_2-emitting industries, such as major power utilities, can minimize their exposure to this risk will be critical to the success of widespread CCS technology. Accordingly, future research should focus on understanding the sensitivity of CCS infrastructure to reservoir uncertainty. Here, we have identified how geologic uncertainty affects the costs and spatial deployment of CCS infrastructure. Specifically, we have shown that sink uncertainty alone produces widely diverging infrastructure solutions each time the *SimCCS* model is executed. Clearly, this is an important effect and needs to be studied in greater detail if CCS technology is going to be deployed at an industrial-scale. Two lines of further research to the impact of geologic uncertainty are evident. First, the impact of modifying existing CCS infrastructure has to be quantified. For instance, how much extra CCS infrastructure investment (e.g., build additional pipelines, open more sinks, drill new injection wells) has to be made to reroute CO_2 stranded at one or more sources? Similarly, it might even be cost effective to open new storage reservoirs if an existing sink incurs unexpectedly high injection costs, even though it has suitable storage capacity. Second, once it is possible to quantify impacts, research should focus on designing CCS infrastructure that a priori is robust to natural uncertainty. For example, a CCS infrastructure model might build excess pipeline capacity or routes into the network in areas that have low expected injection/storage costs but with high uncertainty—that way the system is able to minimize costs as well as respond to infrastructure changes. Likewise, more conservative reservoir capacity estimates might guide a model to identify spatially co-located groups of good reservoirs that can act as alternative storage sites, as opposed to emphasizing an excellent-but-isolated reservoir. In addition, such models should be able to incorporate uncertainty on the source term, to design a CCS network that handles CO_2 produced by future sources that were not foreseen at the beginning of the project. Several models already exist that can deploy CCS infrastructure over time given known future CO_2 emission scenarios (e.g., Klokk et al., 2010; Middleton et al., 2011b; Morbee et al., 2010; van den Broek et al., 2010). These models could be adapted to understand how infrastructure adapts in the future to unforeseen events (e.g., reservoir filling faster than expected or catastrophic failure) especially with high discount rates. Temporal models could also incorporate the effect of a dynamic CO_2 price for enhanced oil recovery (EOR) over time (e.g., as the market for EOR becomes saturated, the price of CO_2 will drop precipitously).

This study has focused on two main areas: (1) understanding how uncertainty in geologic parameters (e.g., permeability, porosity) effects reservoir capacity and cost calculations, and (2) how variability in reservoir characterization leads to substantial variability in the CO_2 capture and storage infrastructure. Further research is required to answer some specific, yet critical, questions. For example, this oil shale study used a set of nine storage reservoirs between 70 and 150 km west of the single CO_2 emissions source. This configuration of sources and sinks is a good test bed for isolating the impact on transport and storage infrastructure, however, other source–sink configurations are much less homogeneous (e.g., Middleton and Bielicki, 2009; Middleton et al., 2012) and perhaps the impact of geologic certainty is somewhat different. Similarly, with more complex source–sink arrangements, future research could identify configurations of sources–pipelines–sinks that are more robust to uncertainty through the CCS system. As a result, commercial-scale CCS operators could minimize their investment uncertainty. Future research could also focus attention on identifying specific drivers of uncertainty—for instance, if the principal sources of uncertainty (e.g., reservoir permeability, formation heterogeneity) that cause infrastructure variability could be identified, then it will be possible to distinguish where uncertainty reduction efforts should be targeted.

6. Conclusions

Cost and capacity uncertainty for geologic reservoirs is a critical consideration for design and construction of large-scale CCS systems. Variation of reservoir permeability within typical ranges can produce a factor-of-ten change in storage costs. Likewise, uncertainty in other reservoir parameters that affect capacity and injectivity (e.g., thickness and porosity) can produce similar cost variation. Industry- or utility-scale CCS development will require a balance between investments to characterize and reduce natural uncertainty and to build flexibility and resilience into transportation networks. In this study, we have shown that uncertainty in geologic properties of storage reservoirs (permeability, thickness, porosity) produces widely diverging CCS infrastructure designs each time the *SimCCS* model is run. Consequently, industrial scale CCS technology will require detailed analysis and modeling that takes into account a large number of different scenarios.

Acknowledgements

The study of carbon management for oil shale production in the Piceance Basin was performed as part of a larger feasibility study of oil shale development within environmental constraints funded by the DOE Office of Naval Petroleum and Oil Shale Reserves. Ongoing development of the *SimCCS* and *CO_2-PENS* models was funded by DOE Office of Fossil Energy through the NETL Carbon Program.

References

Bachu, S., 2003. Screening and ranking of sedimentary basins for sequestration of CO_2 in geological media in response to climate change. Environmental Geology 44, 277–289.

Bachu, S., Bennion, B., 2008. Effects of in situ conditions on relative permeability characteristics of CO_2–brine systems. Environmental Geology 54, 1707–1722.

Birkholzer, J.T., Zhou, Q.L., 2009. Basin-scale hydrogeologic impacts of CO_2 storage: capacity and regulatory implications. International Journal of Greenhouse Gas Control 3, 745–756.

Blackett, R.E., 2004. Geothermal gradient data for Utah. Utah Geological Survey Report, 49 p. http://geology.utah.gov/emp/geothermal/pdf/utah_temp_grad.pdf.

Buscheck, T.A., Sun, Y., Hao, Y., 2011. Combining brine extraction, desalination, and residual brine reinjection with CO_2 storage in saline formations: Implications for pressure management, capacity, and risk mitigation. Energy Procedia 4, 4283–4290.

CRS, 2007. Energy Independence and Security Act of 2007: A summary of major provisions. Congressional Research Service Report, Order Code RL34294. http://energy.senate.gov/public/_files/RL342941.pdf.

Damen, K., Faaij, A., Turkenburg, W., 2006. Health, safety and environmental risks of underground CO_2 storage – overview of mechanisms and current knowledge. Climatic Change 74, 289–318.

EIA, 2010. Crude Oil Production. U.S. Energy Information Administration. http://tonto.eia.doe.gov/dnav/pet/pet_crd_crpdn_adc_mbblpd_a.htm.

EIA, 2010. U.S. carbon dioxide emissions in 2009: A retrospective review. U.S. Energy Information Administration. http://www.eia.doe.gov/oiaf/environment/emissions/carbon/.

Esposito, R.A., Monroe, L.S., Friedman, J.S., 2011. Deployment models for commercialized carbon capture and storage. Environmental Science and Technology 45, 139–146.

Henrikson, A., Chapman, D.S., 2002. Terrestrial heat flow in Utah. University of Utah Report. http://geology.utah.gov/emp/geothermal/pdf/terrestrialhf.pdf.

IEAGHG, 2009. Development of storage coefficients for CO_2 storage in deep saline formations. IEA Greenhouse Gas R&D Programme Technical Report 2009/13, 118 p.

IEAGHG, 2011. International Test Centre (ITC) for CO_2 Capture, IEAGHG RD&D Projects Database. IEAGHG. http://www.CO2captureandstorage.info/project_specific.php?project_id=55.

Johnson, R.C., Mercier, T.J., Brownfield, M.E., Pantea, M.P., Self, J.G., 2009. Assessment of in-place oil shale resources of the Green River Formation, Piceance Basin, western Colorado. U.S. Geological Survey Fact Sheet 2009–3012, 6 p.

Keating, G.N., Middleton, R.S., Stauffer, P.H., Viswanathan, H.S., Letellier, B.C., Pasqualini, D., Pawar, R.J., Wolfsberg, A.V., 2011a. Mesoscale carbon sequestration site screening and CCS infrastructure analysis. Environmental Science & Technology 45, 215–222.

Keating, G.N., Middleton, R.S., Viswanathan, H.S., Stauffer, P.H., Pawar, R.J., 2011b. How storage uncertainty will drive CCS infrastructure. Energy Procedia 4, 2393–2400.

Klokk, O., Schreiner, P.F., Pages-Bernaus, A., Tomasgard, A., 2010. Optimizing a CO(2) value chain for the Norwegian continental shelf. Energy Policy 38, 6604–6614.

Kuby, M.J., Bielicki, J.M., Middleton, R.S., 2011a. Optimal spatial deployment of CO_2 capture and storage given a price on carbon. International Regional Science Review 34, 285–305.

Kuby, M.J., Middleton, R.S., Bielicki, J.M., 2011b. Analysis of cost savings from networking pipelines in CCS infrastructure systems. Energy Procedia 4, 2808–2815.

Letellier, B.C., Sanzo, D., Pawar, R.J., 2010. Statistical abstraction of high-fidelity CO_2 pressure histories in 2-D, uniform, cylindrical domains. In: 9th Annual Conference on Carbon Capture and Sequestration, Pittsburgh, PA.

McCoy, S.T., Rubin, E.S., 2009. Variability and uncertainty in the cost of saline formation storage. Energy Procedia 1, 4151–4158.

Middleton, R.S., Bielicki, J.M., 2009. A scalable infrastructure model for carbon capture and storage: *SimCCS*. Energy Policy 37, 1052–1060.

Middleton, R.S., Bielicki, J.M., Keating, G.N., Pawar, R.J., 2011a. Jumpstarting CCS using refinery CO_2 for enhanced oil recovery. Energy Procedia 4, 2185–2191.

Middleton, R.S., Kuby, M.J., Bielicki, J.M., 2012. Generating candidate networks for optimization: the CO_2 capture and storage optimization problem. Computers, Environment and Urban Systems 61, 18–29.

Middleton, R.S., Wei, R., Kuby, M.J., Keating, G.N., Pawar, R.J., 2011b. A dynamic model for optimally phasing in CCS infrastructure. Environmental Modeling and Software In review.

Morbee, J., Serpa, J., Tzimas, E., 2010. The evolution of the extent and the investment requirements of a trans-European CO_2 transport network. European Commission Joint Research Centre JRC Scientific and Technical Reports (EUR collection). http://publications.jrc.ec.europa.eu/repository/handle/111111111/15100.

NETL, 2010. FutureGen Industrial Alliance Announces Carbon Storage Site Selection Process for FutureGen 2.0. National Energy Technology Laboratory. http://www.netl.doe.gov/technologies/coalpower/futuregen/index.html.

NETL, 2010. Site screening, site selection, and initial characterization for storage of CO_2 in deep geologic formations. National Energy Technology Laboratory Report DOE/NETL-401/090808, 110 p.

Pacala, S., Socolow, R., 2004. Stabilization wedges: solving the climate problem for the next 50 years with current technologies. Science 305, 968–972.

Phillips, B.R., Middleton, R.S., 2011. SimWIND: a geospatial infrastructure model for optimizing wind power generation and transmission. Energy Policy, In review.

Simbeck, D.R., McDonald, M., 2001. Existing coal power plant retrofit CO_2 control options analysis. In: Williams, D.D., McMullan, B., Paulson, P., Smith, C.A. (Eds.), 5th International Conference on Greenhouse Gas Control Technologies. CSIRO, Cairns, Australia, pp. 103–108.

Stauffer, P.H., Keating, G.N., Middleton, R.S., Viswanathan, H.S., Berchtold, K.A., Singh, R.P., Mancino, A., Pawar, R.J., 2011a. Greening coal: breakthroughs and challenges of CCS. Environmental Science and Technology 45, 8597–8604.

Stauffer, P.H., Pawar, R.J., Surdam, R.C., Jiao, Z., Deng, H., Lettelier, B.C., Viswanathan, H.S., Sanzo, D.L., Keating, G.N., 2011b. Application of the *CO_2-PENS* risk analysis tool to the Rock Springs Uplift, Wyoming. Energy Procedia 4, 4084–4091.

Stauffer, P.H., Viswanathan, H.S., Pawar, R.J., Guthrie, G.D., 2009. A system model for geologic sequestration of carbon dioxide. Environmental Science and Technology 43, 565–570.

Surdam, R.S., Jiao, Z., Stauffer, P.H., Miller, T.A., 2009. An integrated strategy for carbon management combining geological CO_2 sequestration, displaced fluid production, and water treatment. Wyoming Geological Survey Report WSGS-2009-CGRD-08.

USEPA, 2010. Emissions & Generation Resource Integrated Database (eGRID). United States Environmental Protection Agency. http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html.

van den Broek, M., Brederode, E., Ramirez, A., Kramers, L., van der Kuip, M., Wildenborg, T., Turkenburg, W., Faaij, A., 2010. Designing a cost-effective CO_2 storage infrastructure using a GIS based linear optimization energy model. Environmental Modelling & Software 25, 1754–1768.

Venteris, E.R., Carter, K.M., 2009. Assessing spatial uncertainty in reservoir characterization for carbon sequestration planning using public well-log data: a case study. Environmental Geosciences 16, 211–234.

Viswanathan, H.S., Pawar, R.J., Stauffer, P.H., Kaszuba, J.P., Carey, J.W., Olsen, S.C., Keating, G.N., Kavetski, D., Guthrie, G.D., 2008. Development of a hybrid process and system model for the assessment of wellbore leakage at a geologic CO_2 sequestration site. Environmental Science & Technology 42, 7280–7286.

Viswanathan, H.S., Robinson, B.A., Gable, C.W., Carey, J.W., 2003. A geostatistical modeling study of the effect of heterogeneity on radionuclide transport in the unsaturated zone, Yucca Mountain. Journal of Contaminant Hydrology 62-3, 319–336.

Yamamoto, H., Zhang, K., Karasaki, K., Marui, A., Uehara, H., Nishikawa, N., 2009. Numerical investigation concerning the impact of CO_2 geologic storage on regional groundwater flow. International Journal of Greenhouse Gas Control 3, 586–599.

Zyvoloski, G.A., 2007. FEHM: a control volume finite element code for simulating subsurface multi-phase multi-fluid heat and mass transfer. Los Alamos National Laboratory Report LA-UR-07-3359. http://fehm.lanl.gov.

Zyvoloski, G.A., Robinson, B.A., Dash, Z.V., Trease, L.L., 1997. Summary of the models and methods for the FEHM application-A finite-element heat- and mass-transfer code. Los Alamos National Laboratory Report LA-13307-MS. http://fehm.lanl.gov.